

Exhibit 2

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UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA, SAN JOSE DIVISION

IN RE: HIGH-TECH EMPLOYEE No. 11-CV-2509-LHK
ANTITRUST LITIGATION

CONFIDENTIAL PORTIONS DESIGNATED

Continued Videotaped Deposition of EDWARD E.
LEAMER, PH.D., Volume 3, taken at the offices
of O'Melvey & Myers LLP, Two Embarcadero Center,
Suite 2800, San Francisco, California commencing
at 9:03 a.m., on Monday, November 18, 2013,
before Leslie Rockwood, RPR, CSR No. 3462.

JOB No. 1765129
PAGES 857 - 1169

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1 October 28th, 2013.

2 A. I'm sorry, which exhibit?

3 Q. Exhibit 2.

4 A. 2. Okay, yes.

5 Q. Exhibit 2 includes the compensation model that 10:53:40
6 you used to compute damages in this case; correct?

7 A. That's correct.

8 Q. Let's look at variable 19, the log of age in
9 years. And this is, as you said on paragraph 19, what
10 this coefficient reflects is how age is related to 10:54:10
11 compensation absent the agreements; correct?

12 A. I don't think that's completely correct because
13 I think you have to realize that coefficient is what's
14 called a partial coefficient or partial regression,
15 meaning that controlling for all the other variables in 10:54:32
16 the equation, that's the coefficient that age wants to
17 have.

18 Q. Right. So controlling for all the other
19 variables in the model, the variable for the log of age
20 for years is shown as a negative .6561; correct? 10:54:48

21 A. That's correct.

22 Q. And so this negative coefficient means that all
23 other things being equal, as the employee ages, the less
24 they are expected to be paid; correct?

25 A. That's, I think, a bit misleading. I understand 10:55:11

1 that data -- this is not an error in computing that
2 coefficient. This model is estimated from exactly the
3 same models that you -- that you referred to a minute ago
4 in which the coefficient on age is positive and the
5 coefficient on age squared is negative, thus using 10:55:32
6 exactly the same data, the data set embodies that shape
7 that you imagine is there. That's embodied in Exhibit 2.

8 But the thing is, is that you've got a bunch of
9 other variables in Exhibit 2 that you didn't have in
10 those simple year-by-year regressions that we saw 10:55:50
11 previously.

12 So you have to be extremely careful in
13 interpreting those coefficients because they're very
14 complex animals in this -- in this setting.

15 Q. So you would agree with me that this shows a 10:56:03
16 negative coefficient which in your model would mean that
17 two employees at the same defendant with the same tenure,
18 everything else in the model being equal, the model
19 estimates that the older worker would be paid less;
20 correct? 10:56:22

21 MR. GLACKIN: Object to the form.

22 THE WITNESS: That is not correct.

23 Q. BY MR. RILEY: Why is that not correct?

24 A. Well, if you said -- if you formed the predicted
25 compensation using this model and then you looked at the 10:56:28

1 age compensation distribution, it's going to very closely
2 reproduce the sample. And the reason that this is
3 confusing -- believe me, I was worried about this, too.
4 And you need to know that this is very dependent on the
5 lag structure that we have here. 10:56:50

6 So the age is going to be to some extent picked
7 up by how much you earned the previous year. Age is
8 going to be picked up to some extent how much you earned
9 by the year before that. So age is entering into this
10 calculation of very complex way through these lag effects 10:57:08
11 as well.

12 Q. So these variables are interdependent, then?

13 MR. GLACKIN: Object to the form.

14 THE WITNESS: I think the better way of saying
15 it is the interpretation is interdependent. It's a naive 10:57:19
16 interpretation is the one that you suggested, which is
17 that this model would imply that the age earnings profile
18 is upside down. And trust me, the model overall doesn't
19 have that.

20 The peculiar feature is that that age 10:57:35
21 coefficient has that sign, and it has to do in this case
22 with the dynamical model that's being estimated. We
23 know -- we know that if you didn't have the dynamics in
24 there and you did it year by year, you'd get that upward
25 sloping profile that you'd expect. 10:57:52

1 science, but your intuition with regard to science is
2 really about simple correlations, not partial
3 correlations, which are what these coefficients are.

4 So I decided to let this thing -- let the data
5 speak, let it determine exactly what mixture of variables 13:19:56
6 is the best one for explaining what -- what level of
7 compensation would normally occur.

8 So it's saying -- let me just be clear. So it's
9 saying that if you hold fixed the San Jose employment
10 sector, the number of transfers among defendants, the 13:20:15
11 number of new hires per number of employees, and all
12 these other variables in the equation, then, like you
13 said, holding everything constant, then this increment
14 is -- has the wrong science.

15 But that hypothetical is a nonsense hypothetical 13:20:31
16 because the real world doesn't behave that way. These
17 things all move together in some complicated way. So you
18 can't make that hypothetical. It's not a sensible
19 hypothetical.

20 Q. Would you expect an increase in hiring at Google 13:20:44
21 to have the same effect on Adobe's employees as on
22 Apple's employees?

23 A. Would I expect? You know, this again addresses
24 the question of how much can you squeeze out of this data
25 set. And in principle, you need to do desegregation. 13:21:02

1 You need to allow for the different firms to have
2 different impacts, which is what you're making a
3 reference to.

4 And I completely agree that in an ideal world,
5 we would desegregate and you would talk about a different 13:21:16
6 data analysis for each of the defendants.

7 But we're not in an ideal world. We're in a
8 world of ten observations or maybe fewer because of the
9 dynamics in the model and way too many variables to allow
10 that to happen. 13:21:34

11 Q. And the problem with aggregation is that you
12 have these effects, such as Google is hiring more people,
13 Adobe is flat or laying people off, and yet it's all
14 combined into one model, into one conduct variable?

15 MR. GLACKIN: Object to the form. 13:21:53

16 Q. BY MR. RILEY: Isn't that the problem?

17 A. I wouldn't call it a problem. That's the
18 assumption that lies behind this model. And
19 alternatively, you haven't said explicitly, but it would
20 be to have the hiring for each one of the defendants in 13:22:04
21 this equation rather than their aggregate. As I said
22 before, in an ideal world, that's exactly what you do.
23 You let the data speak about the differences that the
24 hiring rates for the certain defendants would have on
25 compensation overall, but we're not in the ideal world. 13:22:18

1 mean that it's the truth. It's a function of the
2 specific way in which this model is estimated.

3 Q. And you don't question the accuracy of the
4 estimates that are made here or the computation of
5 undercompensation in Appendix 11C?

14:49:07

6 MR. GLACKIN: Object to the form. Sorry.

7 THE WITNESS: Well, I wouldn't use the blues.

8 Like I said before, I think it's an implausible approach
9 to rely on a data set that suggests that Adobe was harmed
10 and Adobe's employees were helped by these agreements. I 14:49:29
11 think the same is true for Lucasfilm and Pixar.

12 So I think it's very important that you
13 understand that these are not the standard errors that
14 Dr. Murphy would have us compute. These are the standard
15 errors that are too low. So this particular display 14:49:44
16 understates the amount of uncertainty that applies to
17 these coefficients.

18 So if you saw the amount of uncertainty that
19 applies to each one of those coefficients, you might be
20 taken aback by what this disaggregation has done, and 14:49:59
21 allows wild estimates that have -- the symptom of the
22 overestimate -- over-parameterization are two, two
23 symptoms. One is wild estimates; the other one is large
24 standard errors.

25 And you can see the wild estimates, and then the 14:50:16

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1 question is, all right, if you had the correct standard
2 errors, what's the story there.

3 Q. BY MR. RILEY: But isn't it an equally
4 supportable inference that what this shows is that the
5 basic model on which you have founded your conclusions is 14:50:28
6 not reliable?

7 A. That's not true at all.

8 Q. Because once you disaggregate it, which you say
9 is the ideal solution, it produces results which are
10 fundamentally inconsistent with your theory? 14:50:43

11 A. What's ideal is a data set that allows the
12 desegregation to occur. That is a data set that doesn't
13 allow it. You can always play this game of overwhelming
14 a regression by adding more variables. And then you're
15 going to get nonsense results and you're going to get big 14:50:59
16 standard errors.

17 So the possibility that you could do that is
18 really irrelevant to the game here. So the problem with
19 this regression is Dr. Murphy -- this case is not as bad
20 as the other one. The other one is egregious in terms of 14:51:10
21 the number of additional variables they added into the
22 equation. This, to my mind, is still too much
23 desegregation.

24 You're trying to estimate a separate
25 coefficient, a separate conduct coefficient for each of 14:51:23

1 the defendants, and the data, unfortunately, don't allow
2 that. At least we haven't found a model that would allow
3 that to happen.

4 Q. So in Exhibit 112, then, what you believe is
5 part of the problem here is that the standard errors are 14:51:35
6 too large. Is that your -- is that your criticism?

7 A. Well, so my comment is that when you ask a lot
8 of questions, you get pushback from a weak data set. The
9 pushback is -- comes in the form of saying "I can't do
10 this." The data set says "I cannot do this." How does 14:51:58
11 it tell you that it can't do that? It gives you wild
12 estimates and it gives you big standard errors.

13 So you're trying to find out -- and I agree with
14 your goal. I mean, the ideal goal would be to have a
15 separate estimate that characterizes specific 14:52:14
16 circumstances that Adobe was experiencing and focus in on
17 that very closely. We don't have a data set that can do
18 that.

19 So I agree with your goal, but if you go down
20 that path without realization of what you're doing to the 14:52:26
21 inferences, namely, do you get wild conclusions and big
22 standard errors, that's inappropriate. You have to have
23 some wisdom that allows some differences among the firms
24 but not as much as this.

25 So what I've done is I've tried to think what it 14:52:41

1 THE WITNESS: I don't consider it misleading.

2 This is completely accurate. The question is whether you
3 understand what it means, and I worry that you don't.

4 MR. MITTELSTAEDT: Move to strike all of that.

5 Q. Econ 1 is the author of these notes, and you're 15:48:45
6 the one who approved the notes; correct?

7 A. That's correct.

8 Q. Now if you look at line 27 and 28, those are two
9 of the variables that Econ 1 used in this regression; is
10 that correct? 15:49:08

11 A. At my request.

12 Q. And why did you use both of those variables?

13 A. They measure potentially different things.

14 Q. Okay. What does the first one measure?

15 A. It's the rate of hiring, that is, new hires in a 15:49:27
16 firm relative to the employees in the previous year.

17 Q. And the second one?

18 A. It's the number of -- absolute number of new
19 hires.

20 Q. Okay. And your belief is that you need both of 15:49:38
21 them in there to have a reliable regression; is that
22 correct?

23 A. Well, I think that those variables could both
24 play a role in setting of compensation. In other words,
25 it could be that the -- it's the hiring rate that 15:49:53

1 matters, or it could be the absolute number of hiring
2 that really matters.

3 Q. And after running the regression, what
4 conclusion did you come to about the importance of those
5 variables? 15:50:05

6 A. I didn't come to a conclusion with regard to
7 those. As I said before, these are partial regression
8 coefficients, and it's very difficult to interpret the
9 coefficients.

10 So my goal was not to produce an estimate that 15:50:18
11 had all the correct science with regard to the control
12 variables, but instead to let the data form the controls
13 that it sees as most appropriate.

14 Q. Did you reach any conclusion about whether or
15 the extent to which those variables played a role in 15:50:40
16 setting compensation?

17 A. Well --

18 MR. GLACKIN: Object to the form.

19 THE WITNESS: They do play a role. I mean, I
20 don't know whether we're talking about whether the effect 15:50:57
21 is measurable or not, but they help control for the
22 circumstances -- and consequently impact the damage
23 estimate.

24 Q. BY MR. MITTELSTAEDT: Do they play a measurable
25 role? 15:51:07

1 STATE OF CALIFORNIA) ss:

2 COUNTY OF MARIN)
3

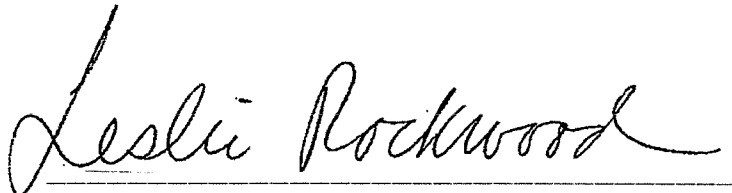
4 I, LESLIE ROCKWOOD, CSR NO. 3452, do hereby
5 certify:

6 That the foregoing deposition testimony was
7 taken before me at the time and place therein set forth
8 and at which time the witness was administered the oath;

9 That testimony of the witness and all objections
10 made by counsel at the time of the examination were
11 recorded stenographically by me, and were thereafter
12 transcribed under my direction and supervision, and that
13 the foregoing pages contain a full, true and accurate
14 record of all proceedings and testimony to the best of my
15 skill and ability.

16 I further certify that I am neither counsel for
17 any party to said action, nor am I related to any party
18 to said action, nor am I in any way interested in the
19 outcome thereof.

20 IN WITNESS WHEREOF, I have subscribed my name
21 this 20th day of November, 2013.

22
23 
24

25 LESLIE ROCKWOOD, RPR, CSR NO. 3462

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